ADDENDUM 1

Original Project Year 4 (2008-2010)

Redesigning the American Neighborhood:

Cost Effectiveness of Interventions in Stormwater Management at Different Scales

Project No. EM97155901

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1. Introduction

This addendum summarizes work done on two RAN program components that were not completed at the time of the final report submitted 7 December 2010, at the close of the final no-cost extension period. These components are 1) results from the efforts to model surface washoff in the Butler Farms and Oak Creek Village neighborhoods and 2) loading analyses for the Englesby Brook detention pond assessment. The work completed on each of these project are detailed in the sections that follow.

2. Project Accomplishments

2.1 Modeling Sediment and Solute Surface Washoff in the Butler Farms and Oak Creek Village Neighborhoods (BF/ OCV)

We have now finalized our flow ratings for the two pipes in which field equipment had been installed, sensitivity analysis and model calibration for our BF/OCV Stormwater Management Model (SWMM) model, and total suspended sediments (TSS) export modeling within the BF/OCV drainage areas.

2.1.1 Drainage Pipe Surveying

Flow-weighted storm sampling within the East and West storm drains in the 2008-2009 field seasons relied on gravity flow equations to compute discharge from stage measurements taken within the storm pipes (Figure 1). For these equations, we used pipe slope values taken from an earlier engineering assessment report commissioned by the City of South Burlington. In our subsequent analysis we came to suspect these pipe slope values were erroneously high, resulting in overestimation of discharge. Thus we resurveyed both pipes in which we had installed instrumentation, using a CST-Berger® 32x SAL Automatic Level (+/- 1.0mm accuracy @ 1km run) and a Sokkia survey rod. The resulting pipe slope estimates were lower than previously reported values for both pipes, and the updated values have been used to re-compute pipe discharges for all subsequent analyses.

Figure 1. West Drain (red outline at left) and East Drain (red outline at right) subcatchment drainage areas.

2.1.2 SWMM Sensitivity Analyses

The SWMM model constructed to simulate the BF/OCV drainage area consists of 20 discrete subcatchments, each with more than a dozen hydrologic and water quality parameters that must be specified. The values for most of these parameters are uncertain and the degree to which this parameter uncertainty affects the model outputs is not completely known in advance. To focus the model calibration efforts on parameters that most affect model outputs and to quantify our projections of uncertainty in model outputs as result of uncertain model inputs, it was important to assess the sensitivity of the particular model structure being used. In this study, we used the Regionalized Sensitivity Analysis (RSA) approach, as described by Wagener et al. (2001), to assess the sensitivity of SWMM outputs to concurrent changes in input parameters.

The RSA approach consists of first running a large number of model simulations, with each included input parameter being randomly drawn from a predefined range for each model run. Other parameters that are not of interest remain fixed during these simulations. For each run, one or more goodness of fit measures are then computed to quantify of the effect of the input parameter set on the model output of interest (e.g. goodness of simulated hydrograph fit to measured data). Thus, for each model run there is a set of randomly drawn input parameters and a corresponding measure of model fit. These runs are then sorted based in the goodness of fit measure (i.e. best to worst), and then separated into bins. Five bins have been used here, though the exact number of bins is somewhat arbitrary. This results in a first bin that includes the best performing 1/'n bins' (1/5th in this case) of simulations, a second bin containing the second best 1/'n bins' of simulations, and so on-- with the last bin containing the worst subset of simulations based on the specified measure of model fit.

Lastly, the goodness of fit values within each of the bins are normalized to sum to 1 within each bin, and the cumulative distributions of these normalized goodness of fit measures are plotted against the input parameter values that produced them. A set of RSA plots for BF/OCV East pipe drainage area model (Figure 1) are presented in Figure 2. For these 50,000 simulations of the East drainage area, the dark blue lines show the cumulative distribution of model goodness of fit (root mean squared error (RMSE) of flow in this case, over the parameter range from which that input parameter was sampled. Lightest blue corresponds to the cumulative distributions of model fit within the worst performing bin. Separation between the lines in a given plot indicates that different levels of model performance are associated with different parts of a parameters allowable range (i.e. model performance is sensitive to changes in that parameter). When all of the lines fall on top of one another, this indicates that across the full range of model performances observed, that parameter is equally likely to lie in any part of its feasible range (i.e. model performance is not sensitive to changes in that parameter). A key advantage to this approach is that by varying all parameters concurrently, the resulting sensitivity assessment is not heavily dependent on the specific underlying model parameterization.

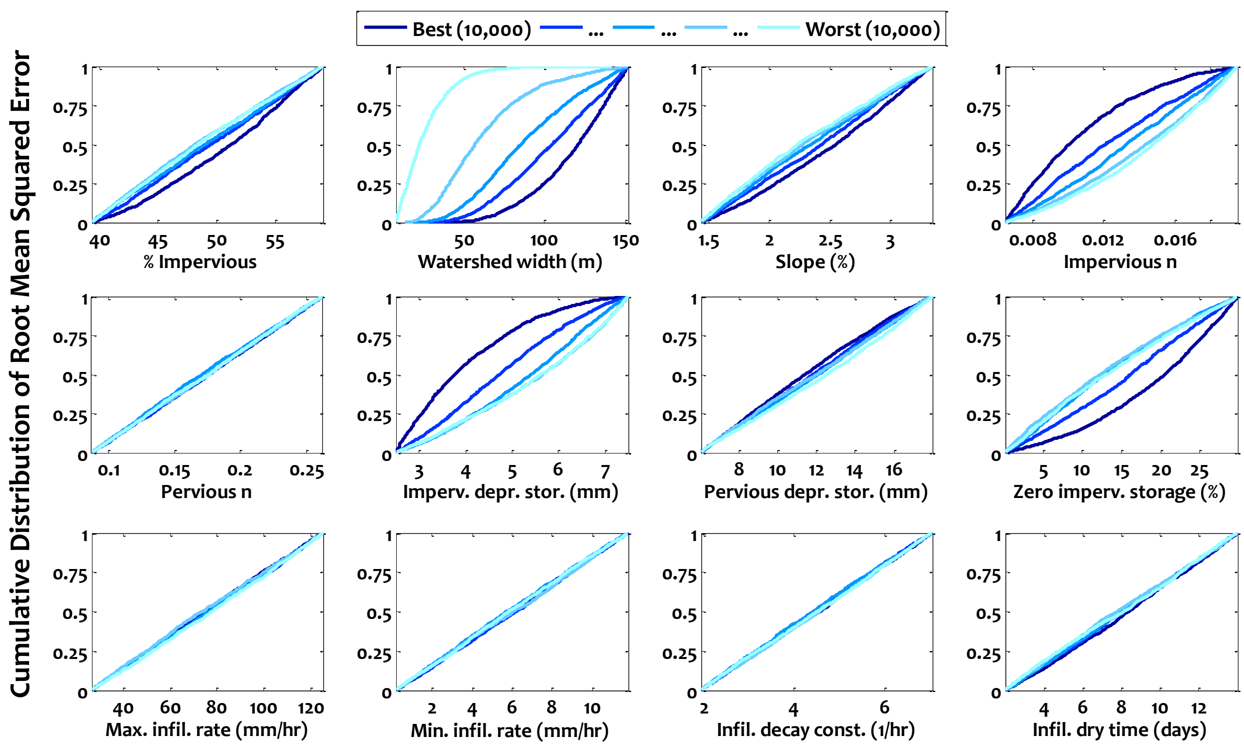

Figure 2. RSA for 50,000 random simulations of the East drainage area BF/OCV SWMM model. The included parameters are selected SWMM surface runoff parameters and soil infiltration parameters under the Horton infiltration model. Model goodness of fit was the root mean squared error of simulated flow. Separation between cumulative distributions for a given parameter indicate sensitivity (e.g. watershed width), whereas a lack of separation (Infil. decay const.) indicates an insensitive parameter.

Cumulatively, the plots in Figure 2 indicate that the East drain hydrology, as measured by RMSE, is most sensitive to watershed width, impervious depression storage, impervious Manning's n, and other parameters to a lesser extent. The soil infiltration parameters appear to have very little influence on model performance based on the RSA plots. This is due to the fact this drainage area is small (1.2 ha), highly impervious (49%), and directly connected to the under-street storm drain in which discharge was measured. Thus, for all but the largest storms, soil infiltration processes are largely irrelevant to modeling the flow of water out of the area via the storm drain (results from the West drain, not shown, are similar). What these results show are that for calibration purposes, the infiltration parameters—even though they are highly uncertain—can be left as best estimates since they do not affect simulated flow.

2.1.3 Model Calibration

The ultimate goal of our sampling and modeling is to extend our measurements from the in-stream monitoring stations and East and West drain sites to characterize surface wash-off loads over the whole residential area within the Potash Brook Tributary 7 study area (Figure 3). To generate neighborhood wide estimates of surface washoff from the available data we first calibrated the East and West drain hydrology using a hybrid random/evolutionary approach. Next, the SWMM buildup and washoff models were calibrated using an evolutionary approach. For each evolutionary calibration run of the buildup/washoff model a different hydrologic parameter set (identified in the preceding hydrologic calibration) was selected and used along with the evolving water quality parameter set. This allowed us to evolve 'best' buildup and washoff model parameters, but independent of any single best underlying hydrologic parameter set. The hydrologic and water quality parameter sets, evolved to best match the measured data in the East and West drains, were then transferred to the other portions of the BF/OCV neighborhoods for which discretized measured data are unavailable.

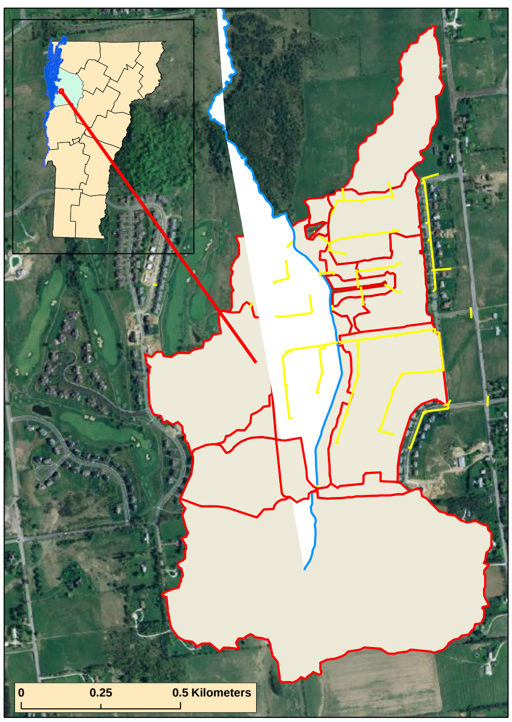

Figure 3. Potash Tributary 7 drainage area with storm drain infrastructure (yellow lines) and discretized SWMM subcatchments (red).

The structure for the SWMM models of the BF/OCV drainage area have evolved over the course of the project. The modeling results presented here are the best available and are based on data from the 2008-09 field seasons.

<u>*Hybrid Evolution Strategies Approach*</u>: Our calibration approach is based on an Evolution Strategies (ES) algorithm search (Eiben and Smith 2007) at each of the calibration steps, with a modification to deal with uncertain parameters which did not evolve to best values. Evolution strategies are a population based approach to parameter search, distinguished among the larger class of

evolutionary algorithms by a heavy reliance on mutation rather than crossover or parameter swapping. ES is particularly well suited for model parameters that take a continuous floating point representation as nearly all of the SWMM calibration parameters do. Initial work applying an ES approach to SWMM parameter search demonstrated that it can consistently outperform uniform random search based on the quality of the simulations found in a given number of SWMM iterations.

The modification made to a traditional ES approach here has been to distinguish between three different types of uncertain input parameters:

(1) Parameters to which model outputs of interest (simulated flow, water quality) are not sensitive. These parameters can simply be fixed at best point estimates despite their uncertainty since they do not affect model output
(2) Empirical or data limited parameters to which outputs are sensitive. Manning's roughness coefficients, watershed width, and all buildup/washoff model parameters, for example, strongly affect model output and cannot be directly measured. Their best values are by definition the values the maximize model performance. These parameters should be evolved to 'best' values using ES.
(3) Parameters to which the model is sensitive, but underlying geophysical data exist (e.g. surface slope, percent imperviousness). In these cases the parameters' underlying distribution can be characterized within a GIS, but may be uncertain. For calibration purposes, these parameters are randomly sampled from across their assigned distributions, with the goal of including this uncertainty in the ES calibration of the type (2) parameters. The goal for these parameters is to incorporate the effect of their uncertainty into the calibration, not to identity 'best' values of the parameter

Results from this calibration approach in the East drainage subcatchment are visualized in Figure 4. Each of the three parameters was concurrently evolved over 20 generations (i.e. evolutionary 'batches' of 140 SWMM simulations) using ES to maximize fit between simulated and observed flow in the East drain. Other parameters (not shown) were concurrently evolved or varied randomly during these runs as described above. Watershed width and impervious depression storage (Figure 4 left and center, respectively) evolved from their initial feasible parameter ranges (i.e. 'Generation 1') to converge on relatively narrow sections of their allowable range. This convergence corresponds with improvement in resulting model fit. In contrast, pervious depression storage (right) does not converge. This is due to the fact the pervious area hydrology is not important in simulating the East drainage area's outflow (i.e. there are no 'better' values of this parameter in this context).

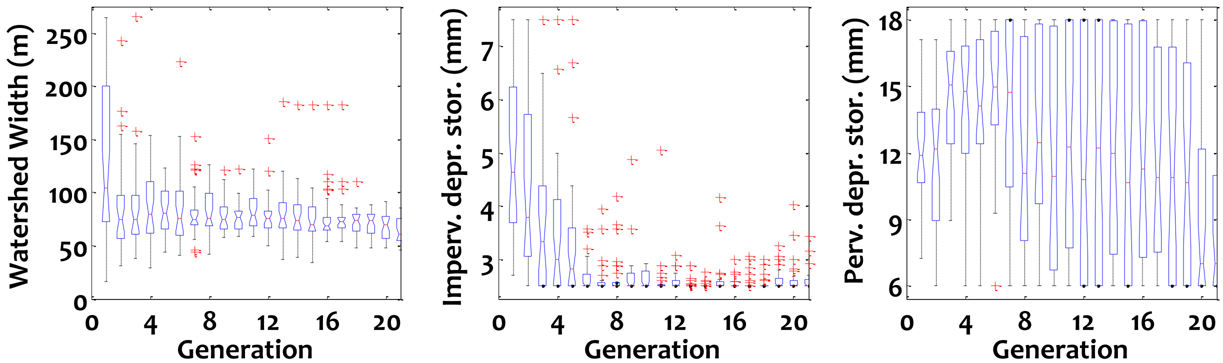

Figure 3. Example of parameter evolution (watershed width and impervious depression storage) and lack of convergence (pervious depression storage). Each boxplot shows the parameter's distribution at the given generation, over a 20 generation run. Boxplots show median (red), IQR (blue), most extreme non-outlier (whiskers) and outliers (+).

For the East and West Drains, the goal of calibration was to develop surface hydrologic parameter sets from the feasible parameter space that would allow for simulation of the other residential portions of the drainage area where discrete time series data were not collected. Several calibration runs were executed in both the East and West drainage areas. Figure 5 shows ten days of observed and model flows in the West Drain. The simulated hydrographs include the best 330 from an ES run that included a total of 1300 simulations. The Figure 5 inset highlights model performance for a storm at the end of the ten day period. It can be seen that the simulations generally under-predict peak flow rates in the observed flow record. During the course of these evolutionary calibration runs, parameters most affecting peak flow rates (e.g. Manning's n, impervious depression storage) tended to evolve to defined upper (or lower) bounds on their ranges that would maximize simulated peak flow rates. The results generally agreed, between multiple ES runs and across sites (i.e. East and West drains), with the surface hydrology parameters in all cases evolving toward values that maximized peak runoff rates.

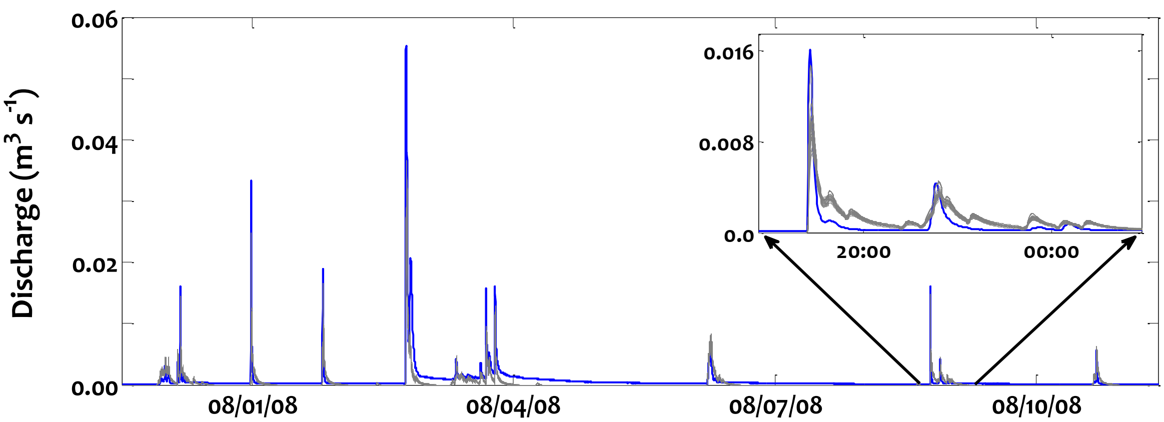

Figure 4. Ten days of observed flow in West Drain (blue line) with 330 best simulated flows (grey lines). Inset hydrograph highlights hydrograph shape for a later storm. These 330 simulated flow series' mean RMSE (fitness) was 0.00102 $m^3\ s^{-1}$.

A model validation check was conducted in the West Drain using the evolved parameter sets shown in the Figure 5. By continuing to run the model for an additional six weeks we were able to calculate the performance of the evolved parameter sets on subsequent storm events not used in the calibration runs. Results are shown in Figure 6. Similar qualitative model performance is seen over the validation period, with peak flow rates either under-predicted or matched. The RMSE over the validation period was actually lower than the RMSE during calibration, however this due in part to the extended periods of dry weather during the following six weeks (i.e. periods of zero flow that were easily matched).

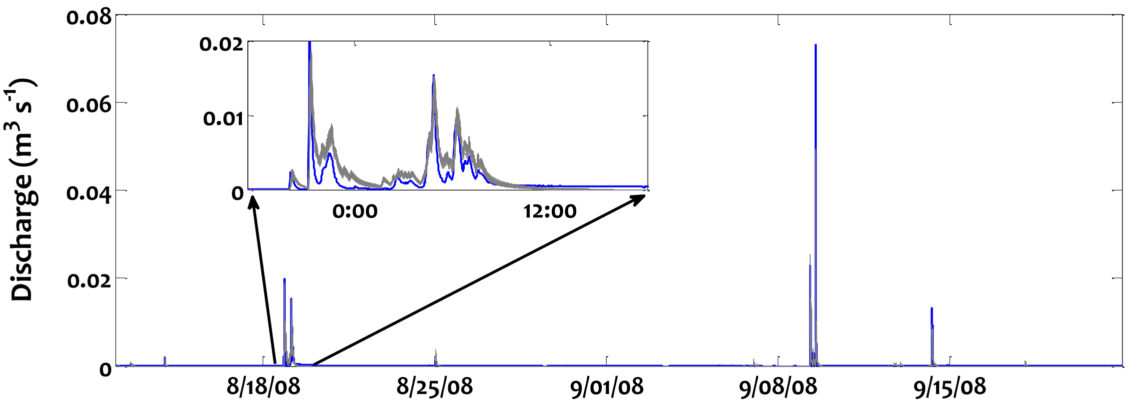

Figure 5. Six weeks of simulated and observed flow in the West Drain validation period. Grey lines show the same simulated hydrographs from the calibration period, extended over the next six weeks. Validation period RMSE was 0.00037 m^3 s^{-1}.

Figures 7 presents simulated and observed hydrographs from the East storm drain over the same ten day calibration period used in the West Drain. Modeled peak flow rates are again consistently lower than those in the observed flow record, and SWMM surface hydrology parameters again evolved toward peak flow rate maximizing sets. Better peak flow fit can be achieved, but only by relaxing assumptions about parameters' upper and lower bounds (e.g. allowing surface Manning's n below 0.009). (Extended hydrograph recessions in Fig. 7 are believed to be the result of a small pool forming behind debris caught on the flow measurement equipment in the East drain pipe. The debris was periodically cleaned out or flushed out by high flow. Thus, no attempt was made to model this behavior.)

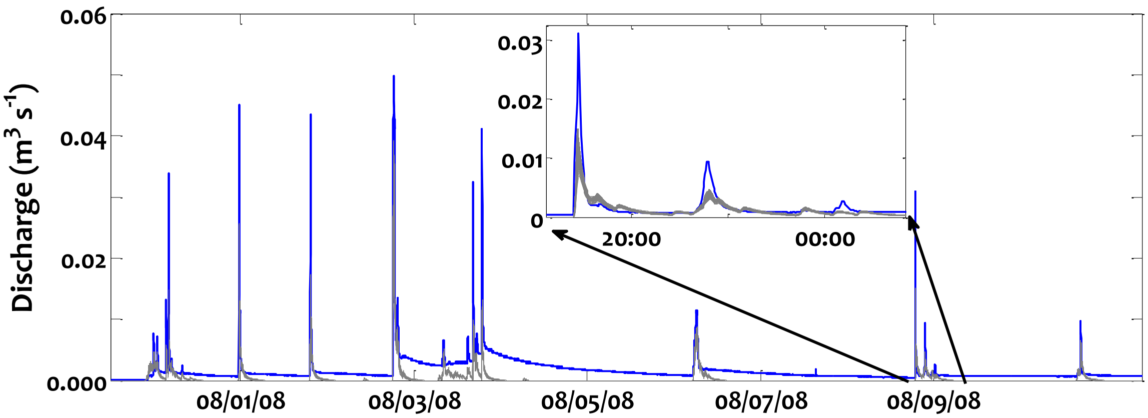

Figure 6. Ten days of observed flow in East Drain (blue line) with 330 best simulated flows (grey lines). Inset hydrograph highlights hydrograph shape for a later storm. These 330 simulated flow series' mean RMSE (fitness) of 0.00194 m^3 s^{-1}.

This calibration process provided the basis for establishing empirical surface hydrology parameter sets for the remaining portions of the BF/OCV neighborhoods. A best subset of parameters from each of the East and West drain ES runs was retained and considered to be a set of likely simulators for the system. These parameter sets were then transferred directly to other portions of the neighborhood. The surface hydrology parameters for which spatial data do exist (e.g. slope, % impervious area) were calculated using GIS data on a subcatchment by subcatchment basis. Either the computed variance or a qualitative estimate of the uncertainty in those parameters' estimates was then taken to be the presumed variance about the mean values. This general framework was used to develop the full neighborhood's hydrologic model.

Water Quality Modeling: An ultimate goal of the hydrologic modeling efforts at BF/OCV is to provide a framework for extending the storm event water quality samples from the East and West Drains to predict loadings from the entirety of the BF/OCV neighborhoods. Thus, similar to the empirical parameter surface hydrology calibrations, the goal of the water quality calibrations was to calibrate the SWMM buildup and washoff (BU/WO) models in the East and West drains and to then transfer those parameterizations to the rest of the BF/OCV neighborhood. The data available for the East and West drain water quality calibrations consists primarily of storm composite event mean concentration (EMC) samples (Table 1, in stream TSS sampling results also shown). We used this sampling approach primarily to reduced analysis costs. However one disadvantage of this sampling approach is that it gives a single average concentration value per

Table 1. TSS EMC samples and calculated loads on mass and mass per unit area bases for all four BF/OCV field monitoring sites. (Upper Site and Trib. 7 Outlet referred to as 'SW1' and 'SW2', resp., in previous reporting.)

Site	Mean TSS (St. err.) *mg/L*	n	Mean TSS Load *kg*	Mean TSS Load *kg/ha-storm*
Upper Site	31.1 (6.1)	26	39.4	0.9
East Drain	58.8 (17.4)	11	2.2	1.8
West Drain	42.2 (10.4)	17	2.4	1.5
Trib. 7 Outlet	36.5 (5.7)	37	104.4	0.9

storm. For model calibration purposes, there may be many disparate BU/WO parameter sets that result in the same average value over the period of the storm, but with very different intra-storm dynamics. In that case, we have no basis upon which to discriminate between better and worse parameter sets or model performance.

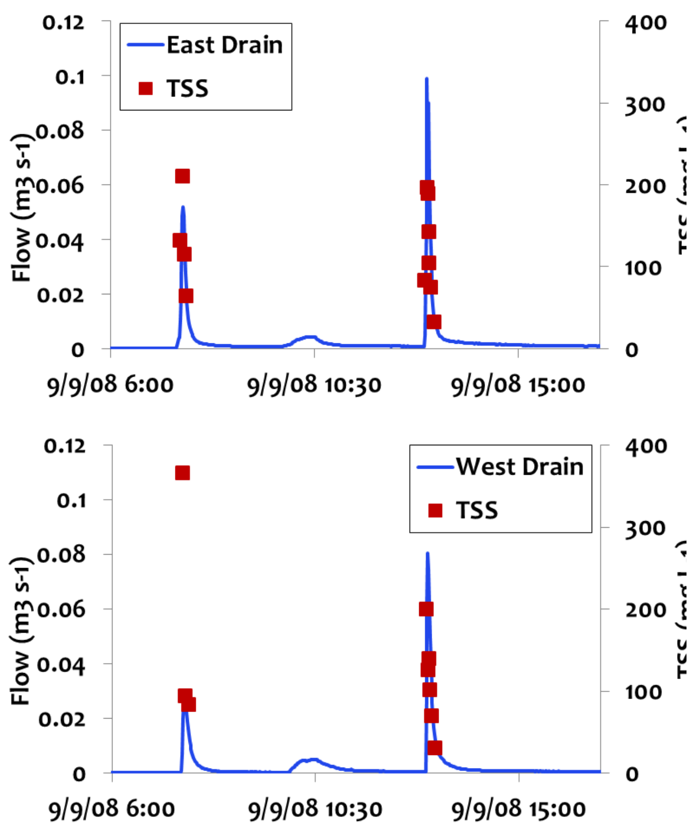

Figure 8. Flow and discrete TSS samples collected from within the East and West drainages areas. Peak TSS concentrations can be seen to roughly correspond with peak flow rates.

For a single storm event we deployed autosamplers in discrete sample mode, with samples collected individually through time rather than being composited into single samples (Figure 8). These data show the intra-storm washoff dynamics for total suspended sediment (TSS) and provide valuable information for BU/WO calibration, which would otherwise be impossible to do with the larger EMC data set alone. By matching the simulated flow of pollutants to these sample concentrations in addition to event averages we have a greater degree of confidence in the model results than by matching storm averages alone.

For the TSS calibration we used an ES algorithm on the BU/WO model coefficients and exponents, assuming an underlying exponential model in both cases. Model performance was assessed based on the difference between the simulated maximum TSS concentrations during the first and third storm pulses (shown in Figure 8), along with 1 summer storm's EMC for each site. The date of the additional summer storm differed between the East and West calibrations. For the goodness of fit measure we used the absolute difference between the simulated and observed concentrations at the two peaks in Figure 8, plus the one additional EMC storm, all summed to give a single error measure in units of mg/L. We used the simulated maximum within +/- 10 minutes of the observed maximum TSS to not penalize small differences in timing.

The ES algorithm allowed us to quickly and repeatedly identify BU/WO parameter sets with goodness of fit measures as low as 11 and 12 mg/L cumulative absolute errors in the East and West subcatchments, respectively. Parameter sets resulting in cumulative absolute error of less than 50 mg/L at either the East or West sites were retained as likely simulators of the system and pooled to create a larger set of BU/WO parameter sets. Frequency histograms of the 567 unique TSS parameter sets that were retained as good simulators of the system are shown in Figure 9. It can be seen that for all four parameters, at least a portion of the predefined parameter space was found to yield better results than the entirety of the allowable parameter space.

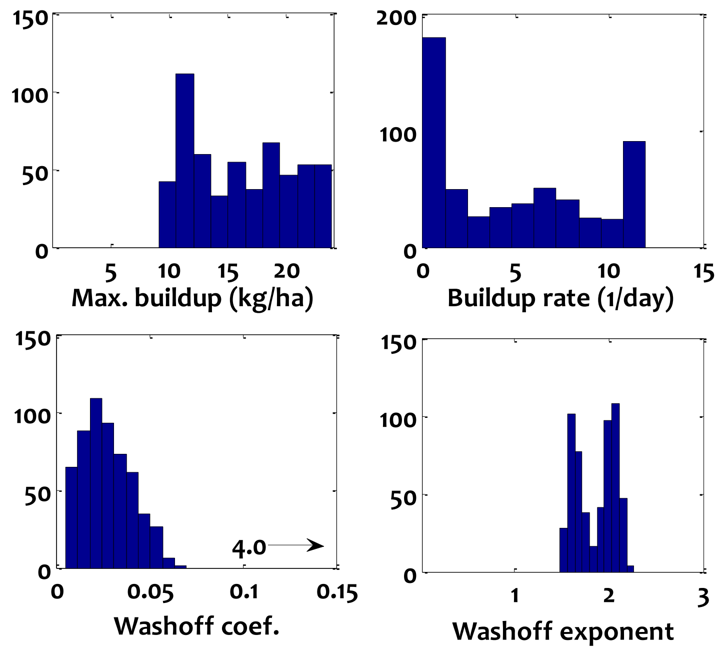

Figure 7. Frequency histograms of the 567 unique TSS parameter sets resulting in less than 50 mg/L cumulative absolute error over the calibration events in East and West drain subcatchments. X-axis limits bound the space over which the parameters were free to evolve, EXCEPT 'Washoff coef.' which was upper bounded at 4.0.

A limited model validation was executed for TSS using the entire pooled set of retained parameter sets (Figure 9), and running them though both the East and West drain models, while concurrently varying the underlying surface hydrologic parameters. The difference between simulated and measured TSS EMCs was then computed for two additional events not used in calibration. Absolute differences for the two validation events averaged 25 and 59 mg/L for the East drainage, and 39 and 16 mg/L in the West drainage over a total of 5,000 simulations. While these absolute concentration errors are higher than we observed during the calibration periods, this was not unexpected. These runs used the pooled set of BU/WO parameters (i.e. best parameters from West calibration input to the East model, and vice versa), so that validation runs included parameter sets at each site confirmed via calibration at the other drain site. As a result, these errors give an indication of the level of error present when transferring subarea-specific calibrations to other parts of the neighborhood.

2.1.4 Neighborhood Washoff Estimates

The calibrated East and West drainage area SWMM models were used to estimate cumulative neighborhood washoff. To do this, empirical surface hydrology parameters were transferred from the East and West drain calibrations to 10 other SWMM subcatchments representing the remaining portions of the BF/OCV neighborhood. Other geophysical parameters (e.g. areas, slope) were estimated from GIS data layers and assigned uniform probability distributions to characterize the uncertainty in those estimates. For each neighborhood washoff simulation, the uncertain geophysical parameters to which model outputs were previously found to be sensitive were randomly drawn from these uniform probability distributions. For the empirical surface parameters and the BU/WO model parameters, the calibration sets from the East and West drain calibration runs were used to establish the possible unique parameter sets for each of these components. Each neighborhood simulation was then parameterized by randomly selecting a pair of these parameter sets (one empirical surface hydrology set and one BU/WO set), which was then joined with the randomly generated parameters, and used to run the model and generate a single model output. Taken together, this approach best allows us to incorporate what we know about model sensitivity and input parameter uncertainty into our model outputs, while also limiting the number of parameters to be concurrently varied.

We ran the calibrated and validated model for 1,000 iterations using our 2008-2009 meteorological data. From the outputs we then summed the predicted TSS export from all 12 SWMM subcatchments representing the BFOCV neighborhood. Predicted TSS was then summed at the lower in-stream monitoring station (Table 1), on a mass loading basis over all of the storm events in the period of simulation for which we have measured data. The measured data (in-stream) give us an estimate of the mass of sediment exported by the Potash Trib. 7 on an event basis. By comparing these measured loads to total neighborhood washoff estimated by the model, we can estimate how much the untreated neighborhood washoff in BF/OCV contributes to total watershed loads. These data are summarized in Figure 10.

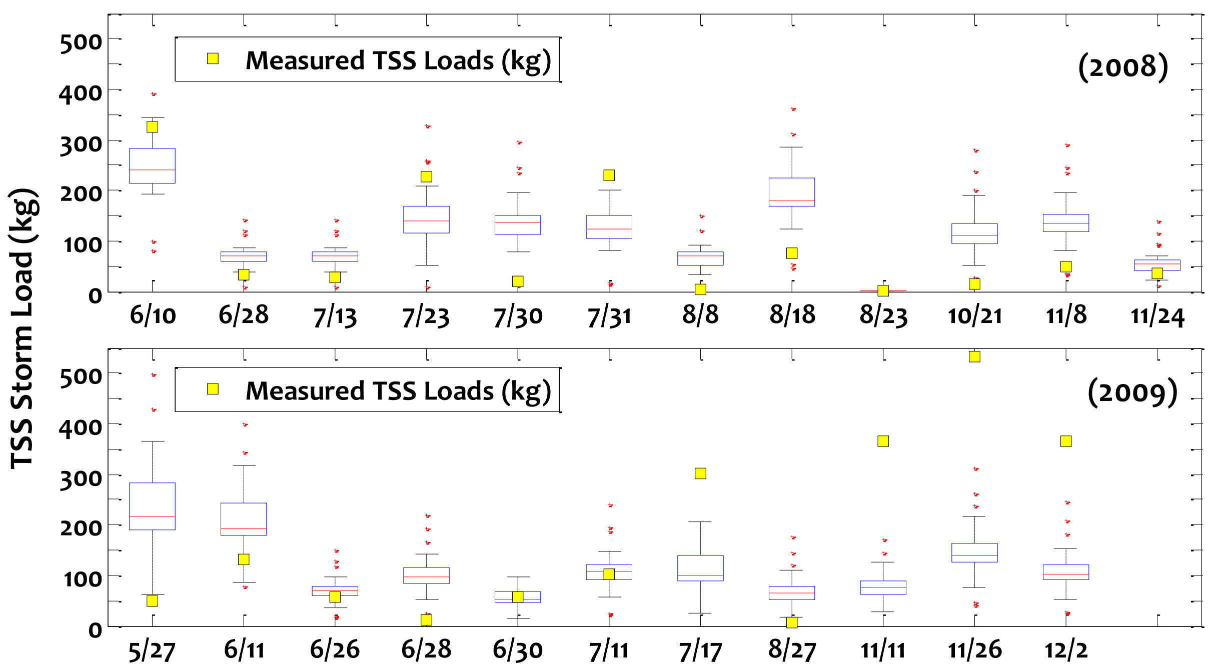

Figure 8. Boxplots showing distributions of model predicted sediment loads delivered to the stream channel via surface washoff from the BF/OCV neighborhoods. Boxplots show median values (red), IQR (blue), most extreme non-outlier (whiskers) and outliers (+). The yellow squares indicate the measured in-stream sediment loads at the drainage area outlet.

It can be seen in Figure 10 that on an event basis the distributions of model-estimated neighborhood washoff account for anywhere from ~20%, to several times the amount of sediment measured flowing past the lower monitoring site. In more than half the events analyzed, the median estimate of total neighborhood washoff exceeds the total estimate of watershed sediment export. Given that the area of the neighborhood accounts for only 36% of the total Potash Tributary 7 drainage area (Fig. 3), it can be inferred that the neighborhood, on a per unit area basis, contributes a disproportionately large fraction of the sediment load. These model results generally correspond with per unit area storm sample data (Table 1), which show that the East and West Drains export sediment at a greater rate, per unit area, than the Upper Site drainage area and the Tributary 7 drainage as a whole. Note that for the Upper Site, Table 1 overstates the export rate because the flow at that site is intermittent. Thus, the flow and sediment flux at the Upper Site was effectively zero for many of the storms sampled in the Drains and at the Tributary 7 Outlet. To the extent that excessive sediment export is a management concern for this area, efforts aimed at neighborhood washoff source reductions or detention/in-transport mitigation may be warranted.

While our modeling approach was designed to corporate as much of the underlying input parameter uncertainty as possible into our estimates, there are some limitations on the interpretation of these data. First, the East and West drainages are the primary basis for our parameterization of the rest of the neighborhood. However, the total area of the East and West drainages combined is only 6% of the neighborhood as a whole. Hydrograph behavior at the watershed outlet suggests that the flow data from the East and West drains are highly representative of the neighborhood runoff responses in general, though there is no comparable basis for the interpretation of East and West drain water sampling data. The spatial proximity and general homogeneity of development in the BF/OCV neighborhoods leads us to believe these drainage areas are representative of the neighborhood as whole. However, drainages that represented a larger portion of the watershed would have been preferred. Initially, in 2007, we did attempt to instrument two other BFF/OCV outfalls, draining a much larger fraction of the neighborhood. However, these outfalls were subject to back-flows that made it impossible to collect reliable flow and water quality data at those sites. For this reason we shifted to the smaller East and West drain sites.

A second limitation in this approach is that transport of sediment is not strictly conservative. It was relatively straightforward for us to bracket the storm flow hydrographs from the drains and from the in-stream monitoring station for comparison of events driven by the same precipitation event. However, the in-stream distance between the farthest upstream neighborhood drain outfall to the lower in-stream sampling site is 880 m. The channel over this distance is alternately densely vegetated,

Figure 11. An actively eroding stream bank in Potash Brook Trib. 7 as it traverses the BF/OCV neighborhoods.

impounded by yard debris, and channeled through culverts in poor condition. Each of these factors adds to the capacity of the channel to provide additional attenuation to the flow of water and transport of sediments. As a result it is entirely likely that the total sediment load delivered to the channel upstream is not conveyed past the lower monitoring station in the same time period as that event's runoff volume. In other words, the hydrological loading and sediment loading may not be synchronized.

It is clear from Figure 10 that at times the total mass of sediment washed off from the neighborhood is greater than the total mass of sediment that leaves the neighborhood at the downstream station. This suggests that at least on a short term basis the stream channel stores sediments washed off from these neighborhoods. It is unlikely that this process can persist over the long term. We've seen no evidence of net channel aggradation in the reach of Potash Trib.7 draining the neighborhood. Rather, the channel is in many reaches deeply incised, with actively eroding banks and scouring near culvert inlets (Figure 11). Thus, we expect there is some combination of winter/spring or large (rare) event net sediment export that has not been fully captured in our sampling or analysis.

2.2 Englesby Brook Detention Pond Performance Assessment

Our previous reporting has covered total nitrogen (TN) and total phosphorus (TP) event mean concentration (EMC) samples collected at the inlet and outlet of the Englesby Brook detention pond. These analyses showed that the pond significantly reduced the means and variances of TN and TP EMCs as the storm flow passed through the pond. Hydrologic imbalances between the detention pond's inlet and outlet led us to question the validity of the flow rating at the pond outlet, and so we concluded that estimates of loadings would be inaccurate. Further investigation by our USGS collaborators identified two issues related to the vortex outlet device that conveys flow out of the pond at lower stage. Additional field measurements in 2011 and subsequent re-analysis allowed us to develop an improved outlet flow series.

2.2.1 Event based loading analysis

For each sampled storm we calculated the mass of phosphorus and nitrogen into and out of the pond based on the EMC sample data and the inlet and outlet pond flow series (Table 2). Over the full set of sampled storms, TN and TP inlet loads were reduced on an event basis by an average of 16% and 54%, respectively. However, these load reduction analyses are of limited validity in cases where the hydrologic load sampled at the inlet and outlet differed substantially. This discrepancy occurs when a storm's total runoff volume flows through the inlet quickly; e.g., several hours, whereas it may take several days for a corresponding volume to pass the outlet. In this cases there was a tendency for the autosampler program to sample a greater fraction of the total runoff volume at the inlet (often corresponding to whole storm events) than at the outlet site (where timing of sample collection often cut off sampling during the pond's draw down). A separate analysis using only the subset of storms in which sampled inlet and outlet storm flow volumes were nearly equivalent yielded only small differences – specifically, slightly greater load reductions. This suggests that these event based reduction estimates are conservative. We viewed this problem as largely unavoidable given the hydrologic dynamics of the pond and the need for timely collection and processing of samples.

Table 1. Event based analysis of Englesby Brook detention pond inlet and outlet loads. Mean and S.E. of storm EMC data, sampled flow volumes, loads, dry weather concentrations, and average reductions are shown for TN and TP at both sites. Differences in *n* result from unreliability in a small section of the flow record.

	TN (mean)	TN (SE)	n	TP (mean)	TP (S.E.)	n
Inlet						
Storm EMC (mg/L)	1.53	(0.13)	45	0.751	(0.114)	44
Sampled Volume (m^3)	1,503	(169)	41	1,502	(173)	40
Storm Load (kg)	2195.8	(364.3)	41	1086.6	(215.4)	40
Dry weather (mg/L)	1.82	(0.42)	6	0.075	(0.020)	7
Outlet						
Storm EMC (mg/L)	1.06	(0.07)	44	0.156	(0.021)	43
Sampled Volume (m^3)	1,202	(159)	40	1,103	(164)	39
Storm Load (kg)	1240.9	(179.2)	40	173.1	(27.7)	39
Dry Weather (mg/L)	1.20	(0.35)	6	0.080	(0.029)	7
% Load Reduction	15.9	(19.4)	40	54.3	(20.7)	39

2.2.2 Long term loading analysis

In addition to the event based analyses, we used the full sets of inlet and outlet nutrient data with the continuous flow records to generate continuous estimates of N and P flux into and out of the pond. The sets of storm EMC samples summarized in Table 2 were used to characterize the expected inlet and outlet concentrations of TN and TP over all storm events in the hydrologic record. Table 2 also shows average concentrations of TN and TP samples collected during 'dry weather' periods. For both the inlet and outlet sites, these included a composite EMC sample collected over a single day in spring, summer and fall (e.g. 75 samples composited over 24 hours). These samples captured the total mass of N and P into and out of the pond on that low flow day from each season. The remaining 'dry weather' samples are single grab samples collected during summer. Cumulatively, these dry weather samples provide a basis for

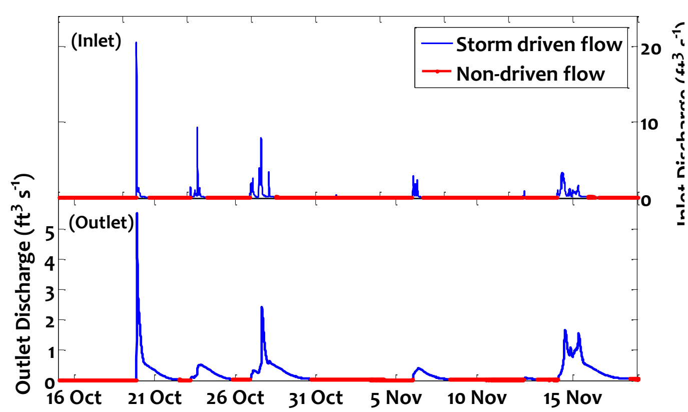

Figure 12. Partitioning of Inlet and Outlet flow series between storm-driven and non-storm driven segments. NOTE DIFFERENCES IN Y-AXIS SCALES.

estimating pond inflow and outflow of TN and TP during non-storm driven periods.

From these data, we calculated long term removal/retention rates of N and P under two scenarios. For both scenarios, the inlet and outlet flow records were first partitioned between storm driven and non-storm driven segments based on absolute discharge and rate of change of discharge thresholds (Figure 12). The period of hydrologic record was also restricted to April 1 through Dec 1 for each of the years of data, due to the limited EMC sample data outside of those dates. The sampled concentration data were then applied to the portioned flow series under the following two scenarios;

Scenario 1: Average of all storm concentrations and average of all dry weather concentrations from entire data set applied to storm driven and non-storm driven flow records, respectively.

Scenario 2: Storm EMC data and 'dry weather' concentrations subdivided by season, with seasonal average concentration data applied to corresponding seasonal portions of the storm driven and non-storm driven flow records. EXCEPT: Outlet site storm driven phosphorus concentrations, which did not have a statistically significant regression with respect to time of year. Pooled average of all outlet storm TP samples (as in scenario 1) was used here.

Table 3. Long term estimates of detention pond TN and TP removal under two scenarios. The period of analysis includes Jun. 8- Dec. 1 2007, Apr 1 – Dec. 1 2008, Apr 1 – Oct 15 2009 (617 days total).

	Scenario	
	1 - Average concentrations	2 - Seasonal Averages
Total Nitrogen		
In		
Storm Driven (kg)	229.8	227.8
Non-Storm Driven (kg)	92.5	89.7
Out		
Storm Driven (kg)	205.2	200.5
Non-Storm Driven (kg)	25.1	20.5
Total Reduction (%)	**28.5**	**30.4**
Total Phosporus		
In		
Storm Driven (kg)	113.6	113.0
Non-Storm Driven (kg)	3.8	5.7
Out		
Storm Driven (kg)	30.1	30.1
Non-Storm Driven (kg)	1.7	2.7
Total Reduction (%)	**72.9**	**72.3**

The results from these two scenarios are presented in Table 3. It can be seen the inclusion of seasonality, relative to a simple average concentration approach, does not substantially alter the estimates for TN and TP load reductions: 28.5-30.4% and 72.3-72.9%, respectively. In this context TP 'removal' is equivalent to long term retention in the pond. For TN, an unquantified fraction of this retained load might be lost to the atmosphere via denitrification over time. Overall, these reduction estimates exceed the TP reductions stipulated in the Vermont Stormwater Manual's Water Quality standard (i.e. 40% TP removal), and either exceed or are commensurate with other published nutrient removal estimates for detention ponds (Comings et al. 2000; Hossain et al. 2005; Mallin et al. 2002; VT-ANR 2002; Weiss et al. 2007; Wu et al. 1996;).

There are two primary qualifications we place on these long term estimates. First, we cannot say how far into the future these removal estimates can be extrapolated. The pond in this study was constructed in 2005 and all sampling was completed within the first five years thereafter. During this period the forebay and main pond were not dredged. However, at some point pond performance could be diminished as a result of either decreased storage due to sediment infilling, or greater nutrient export due to the remobilization of large accumulated reservoirs of N and/or P. Either of these scenarios should be avoidable with adequate pond maintenance. Second, our sampling program did not cover winter periods adequately enough to make estimates about pond performance over that time period. The primary obstacle to winter sampling was ice in the sample intake line, which interfered with sample collection and would have required a heating element along the intake line to overcome. Including a heating element would be worth considering in future studies in cold weather environments. Thus, it is possible that the pond's dynamics over winter differ from what is reported here with respect to N or P removal. Our limited data from December, February and March sampling suggests – but does not prove - that the detention ponds continue to retain TN and TP.

3. Concluding Remarks

In summary, over the duration of the no-cost extension we have been able to complete considerable additional work on the outstanding project objectives. Finalized hydrologic model structures and calibrations for the Butler Farms and Oak Creek Village drainage areas provided the basis for our sediment washoff modeling. In addition, our work with the City of South Burlington and the Butler Farms and Oak Creek Village neighborhoods over the course of this project contributed to the design and implementation of distributed stormwater management solutions in the neighborhoods. While this process did not proceed exactly as we had initially hoped, we have no doubt that our involvement has led to greater awareness around the issues of development, water quality, and stormwater among the residents of BF/OCV, and that we helped to shape the stormwater interventions currently being adopted.

Lastly, our work on the Englesby Brook detention pond assessment has shown that within the scope of our analysis, the pond preforms at high level with regard to reduction of transported TN and TP. While these results were not entirely unexpected, they do offer a degree of justification to the expense associated with siting, constructing, and maintaining the pond and general validation to the stormwater management approaches currently being employed in Vermont.

4. References

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